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Does Ignoring Multi-Destination Trips in the Travel Cost Method Cause a Systematic Downward Bias?

TIMO KUOSMANEN, ELEONORA NILLESEN, JUSTUS WESSELER

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MANSHOLT GRADUATE SCHOOL

Hollandseweg 1, 6706 KN Wageningen,
The Netherlands
Phone: +31 317 48 41 26
Fax: +31 317 48 47 63
Internet: http://www.sls.wau.nl/mi/
e-mail: office.mgs@wur.nl

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Timo Kuosmanen, Eleonora Nillesen, Justus Wesseler*

Environmental Economics and Natural Resources Group, Social Science Department
Wageningen University, Hollandseweg 1, 6706 KN Wageningen
The Netherlands
E-mail: justus.wesseler@wur.nl
Phone: +31 317 482300
Fax: +31 317 484933
*corresponding author

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Abstract

In theory, treating the multi-destination trips (MDTs) as single-destination trips (SDT) does not necessarily lead to biased results, because negative effect of price increase may be offset by the shift of the estimated demand curve. However, in our empirical application of the TCM zonal model to the valuation of the economic benefits of the Bellenden Kerr National Park in Australia we find (statistically significant) evidence that ignoring the MDTs leads to a dramatic overestimation of the consumer surplus. This is in sharp contrast to the earlier empirical evidence from other type of TCM models, which have either excluded the MDT visitors from the data set or treated them as single-destination trips, suggesting the opposite conclusion.

1. INTRODUCTION

The problem of multi-destination trips (MDT) is as old as the travel cost method (TCM) itself. Although the issue has received considerable attention in the TCM literature a satisfactory solution still remains to be found. Indeed, empirical applications of the TCM often do not even consider any correction for MDT bias. Some argue that as though their data set only contained a few MDT visitors they could easily be left out, or treated as if they were single purpose respondents (Loomis and Walsh, 1997). Others believe that any correction would be arbitrary and it would thus be better not to make any correction at all (e.g. Beal, 1995). Nevertheless, considering MDT can be important under particular circumstances. There are studies suggesting that ignoring them can result in an underestimation of the recreational value of 50% and more (Loomis et al., 2000; Mendelsohn et al., 1992).

In the spirit of Hotelling (see Ward and Beal, 2000, pp. 217-218), Mendelsohn et al. (1992) suggest including all alternative sites, and combinations thereof, in the estimation of the demand function, to take into account the substitution possibilities. However, the number of demand equations rises exponentially, and the information to be collected increases tremendously.

Loomis and Walsh (1997) identify two alternatives for estimating a fully-blown demand system. The simpler one is to drop all observations involving multiple destination trips, estimate demand with data of the single destination users, and compute a per-visit consumer surplus figure based on these functions. However, by omitting multi-destination visitors, and thus only including single destination visitors, one is oblivious to the fact that single destination visitors might differ considerably from multi-destination visitors with respect to demographic and socio-economic characteristics. Alternatively, one can try to allocate total costs among multiple destinations. One approach is to use a quantifiable variable, such as ‘nights spent’ at the different sites, as a proxy for relative importance (Knapman and Stanley, 1991; Stoeckl 1993), another, to try to use visitor’s preferences to allocate the cost. Bennett (1995) notes that, although the second approach is much more subjective, it does enable the recognition of the possibility that the importance of visits may not be simply a function of time allocation. Unfortunately, plenty of evidence from experimental studies clearly illustrates the difficulty of expressing preferences in measurable quantities (e.g. Hajkowicz et al., 2000).

The objective of this paper is to shed further light on how the way of dealing with MDT can influence the consumer surplus estimates obtained by the TCM. To this end, three distinct routes will be pursued: First, we seek further analytical depth to this issue by decomposing the MDT effect into two measurable components: the *direct effect* of the price change, and the *indirect effect* of the shift of the empirical demand function. Second, we consider the possibility of using ordinal rankings of the alternative MDT sites as a basis for extracting cardinal cost-shares required by the TCM. In particular, we will re-examine the extreme value approach initially proposed by Kmietowitcz and Pearman (1981) in the present TCM context. Third, we apply the extreme value approach and present some empirical evidence of the influence of the MDTs on the TCM consumer surplus estimates. Using the data of the TCM study for the Bellenden Kerr National Park in Australia by Nillesen et al. (2002), we estimate the theoretical minimum and maximum bounds for the TCM both with and without a MDT-correction, using a parametric weighted-ordinary-least-squares and a non-parametric trapezoid-rule approach for estimating the demand functions.

The rest of the paper unfolds as follows: Section 2 analytically decomposes the effect of MDT on consumer surplus, and concludes that considering MDT will not necessarily increase the consumer surplus. This is followed by an introduction of the modified extreme value approach for MDT, which is then applied to a case study from Australia where about half of the visitors of a National Park visited the park as part of a MDT. We close with a discussion of our results and draw conclusions for the TCM.

2. CONSUMER SURPLUS

Consumer surplus (CS) is a measure of consumer welfare: It is the sum of money consumers were willing to pay for a particular product over what they actually had to pay. Formally, let $x_i : \mathbb{R}_+^{n+1} \to \mathbb{R}_+$ denote the Marshallian demand of commodity *i* as a function of price vector $p : \mathbb{R}_+^n$ and income *I*. Let $\overline{p}_i$ denote the prevailing price for commodity *I*. The consumer surplus of commodity *i* can be written as

$$CS(i) = \int_{\overline{p}_i}^{\infty} x_i \,(p_1, ..., p_n, I) dp_i \,. \tag{1}$$

In other words, CS can be seen as the area under the Marshallian demand curve above the current price level.[2]

The purpose of the TCM approach is to estimate the demand function x_i for the recreational site. We investigate how dealing with multi-destination trips influences the estimated consumer surplus. We compare the 'ideal' situation where the true but

[2] For convenience, the definition above described consumer surplus in terms of Marshallian (market) demand curves rather than Hicksian (compensated) demand curves. Marshallian curves are easier to estimate empirically, and they can reasonably approximate the Hicksian ones for small prices changes and for goods with few substitutes and compliments.

unknown travel cost share is correctly assigned to the destination to the two common approaches of ignoring the multi-destination trips:

1) Respondents with multi-destination visits are omitted from the data.
2) Total travel cost is used without any adjustments to the multi-destination visitation.

The first case does not necessarily involve any systematic error, provided that data availability does not introduce problems. Omitting the multi-destination visitors may have an undesirable side-effect of decreased sample size, but that is a statistical matter which might be taken into account in the design of the study. A more serious difficulty is that the profiles of the single purpose respondents and omitted multi-destination visitors might differ, since the single-purpose visitors tend to live closer to the nature reserve than the multi-destination visitors. In such circumstances, the omission of long-distance multi-destination travelers might leave some important influences of demographic variables undetected because of little variation in the sample. This can also influence the shape of the estimated demand curve, and hence CS estimate. The existing empirical evidence (Loomis et al., 2000; Mendelsohn et al., 1992) unanimously suggests that the omission of MDT visitors from the data set leads to an underestimation of the CS, which can amount up to 50% or higher.

Together, the effects of decreased sample size and the respondent profile may become an issue in zonal models, where it may be difficult to find enough single-destination visitors from distant zones. Therefore, the omission of multi-destination visitors seems a more viable strategy in individual traveler models where plenty of data are available. As the zonal approach is the more often applied one we focus exclusively on the approach without any adjustment to MDT.

In this case, the treatment of MDT influences the consumer surplus in two mutually offsetting ways. We call them the *direct effect* and the *indirect effect*. When the total travel cost is used instead of the effective (correct) cost share, the price of the commodity increases. This has the direct effect of decreasing the consumer surplus: Taking the sub-differential of the consumer surplus we see:

$$\frac{\partial CS(i)}{\partial \overline{p}_i} = -x_i\,(p_1,...,\overline{p}_i,...,p_n,I) \le 0 \;\forall p_1,...,p_n,I \tag{2}$$

Consequently, if total travel costs are used without correcting for the MDT, the prevailing MDT price $\overline{p}_i^M$ will increase to $\overline{p}_i^O (\overline{p}_i^O > \overline{p}_i^M)$, and hence the CS will be smaller. In other words, the direct effect is always non-positive. We can quantify this direct effect as

$$DE = \int_{\overline{p}_i^M}^{\overline{p}_i^O} x_i\,(p_1,...,p_n,I)dp_i \tag{3}$$

However, the previous effect does not take into account the *indirect effect* of the MDT to the estimated demand function x_i. Let $\hat{x}_i^M$ and $\hat{x}_i^O$ denote the demand functions estimated from data adjusted for MDT and omitting adjustment, respectively. Since the observed costs are always lower for the multi-destination adjusted cost data, sensible estimation technique will yield coefficients with the property that

$$\hat{x}_i^M(p_1,...,p_n,I) \le \hat{x}_i^O(p_1,...,p_n,I) \;\forall p_1,...,p_n,I\,. \tag{4}$$

That is, for any given prices and income the estimated demand will be higher if the total cost of travel is assigned to the nature reserve, compared to the case where only the effective fraction of the costs is used. This is because we have the same demand observations in the data, but the price observations are higher in the former case. Typically, we would expect that the slope of the demand curve will be flatter when the travel costs are adjusted for MDT, because the multi-destination trips tend to be more important for the long-distance visitors associated with higher travel costs.

The explicit analytical representation of the latter effect depends, among others, on the estimation technique to be used, the specified function form (if applicable), and the specified error distribution. Given the empirical demand functions $\hat{x}_i^M$ and $\hat{x}_i^O$, we can quantify the indirect effect as

$$IE = \int_{\bar{p}_i^{TC}}^{\infty} \left(\hat{x}_i^O(p_1,...,p_n,I) - \hat{x}_i^M(p_1,...,p_n,I) \right) dp_i \ . \tag{5}$$

INSERT: ***Figure A. Illustration of the direct and the indirect effects.***

Figure A illustrates these effects graphically. The direct effect (*DE*) of accounting for multi-destination trips is due to the price increase from p^M to p^O, given the original demand curve $\hat{x}_i^M$. The indirect effect (*IE*) is the shift of the demand curve from $\hat{x}_i^M$ to $\hat{x}_i^O$, given the new price p^O. Whether accounting for MDT makes a difference, and by how much, depends on the relative difference of the areas *DE* and *IE* in Figure *A*. This is solely an empirical question, which probably depends on the proportion of MDTs in the sample. We address this issue from the empirical perspective in Section 4.

3. WEIGHTING MDT USING THE EXTREME VALUE APPROACH

As the previous discussion illustrated, ignoring MDT can but not necessarily will result in biased estimation of the consumer surplus. In this section we consider the possibility of using ordinal rankings for valuing MDT in TCM. Hajkowicz *et al*., (2000) evaluated five weighting methods, for ranking criteria, applied to multi-criteria decision making in natural resource management. The five methods include fixed point scoring; rating; ordinal ranking; geographical weighting and paired comparisons. Evaluation was based on ease of use, and how much they helped clarify the problem. Their results showed that decision-makers felt most uncomfortable when applying fixed point scoring, i.e. distribute a fixed number of points among the criteria as is occasionally used within TCM (e.g. Willis and Garrod, 1991; Hanley and Ruffell, 1992). Ordinal ranking appeared to be the most preferred method. Hajkowicz *et al*. (2000) hypothesizes that a reason for favoring this method may have been that it does not require anything else than purely ordinal information from decision-makers.

A critical part of using the ordinal information of ranked multiple destinations is allocating part of the total travel costs to one destination. TCM necessitates a conversion of ordinal ranking numbers into cardinal cost-shares. There are several techniques that could be used for this conversion. Nillesen et al. (2002) apply the mean-expected value approach (Rietveld, 1989) in their application of TCM to the valuation of the Bellenden Kerr National Park in Australia. In this paper we adapt the extreme value approach of Kmietowicz and Pearman (1981) to the TCM context. We use these extreme values for sensitivity analysis of the estimated demand curve and the consumer surplus. It is simple to make calculations for two different scenarios, one using the minimum cost shares for all respondents to derive the lower bound estimates, another involving the maximum cost shares to derive the upper bound estimate. If the lower bound does not differ too significantly from the upper bound, we can be assured that the estimated consumer surplus is robust with respect to the treatment of the multi-destination trips. Even if there is considerable deviation, we can use the lower and/or the upper bound for making safe and sound policy inference. Finally, if the estimated range is way too wide to support any sensible conclusions, then at least we can demonstrate a strong case for imposing additional structure and assumptions.

Assume the respondent has visited n destinations, and can rank the destinations in non-increasing ordering according to their importance, i.e., from the most important to the least important. Let the unknown travel-cost shares of each destination be denoted by vector $\gamma = (\gamma_1 \ldots \gamma_n) \in \mathbb{R}^n_+$, satisfying the following properties 1) $\gamma_1 \geq \gamma_2 \geq \ldots \geq \gamma_n$, and 2) $\sum_{i=1}^{n} \gamma_i = 1$.

Let the ranking of the destination we are interested in be $j \in \mathbb{N}_+ : 1 \leq j \leq n$, and the cost share of this destination γ_j. We would like to know the value of γ_j to calculate the effective travel cost to the destination for this particular visitor, but given the ordinal information only, we cannot infer the exact value. But still, we can derive the minimum and the maximum value of γ_j such that all cost shares satisfy conditions 1) and 2). It is straightforward to show (see Kmietowitcz and Pearman, 1981) that

$$\min_{\gamma} \left\{ \gamma_j \,\middle|\, \gamma_1 \geq \gamma_2 \geq \ldots \geq \gamma_n, \sum_{i=1}^{n} \gamma_i = 1 \right\} = \begin{cases} 1/n & \text{for } j = 1 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

and

$$\max_{\gamma}\left\{\gamma_j \,\middle|\, \gamma_1 \geq \gamma_2 \geq \ldots \geq \gamma_n, \sum_{i=1}^{n}\gamma_i = 1\right\} = \frac{1}{j}. \tag{7}$$

These minimum and maximum values characterize the feasible range of the unknown cost share γ_j.

The travel costs of a specific site that was ranked first among several sites would be included by hundred per cent, while the travel costs of a site that was ranked e.g. third would be considered with about 33 per cent.

From the methodological perspective, it is interesting to note that the extreme value approach is well in line with the traditional Hotelling approach that simply excludes multi-destination visitors from the sample. Observe that the minimum weight equals zero, except for the topmost ranking destination. Therefore, if our nature reserve does not typically rank as the primary destination, then the traditional approach comes very close (or even coincides) with our lower bound estimate. In this sense, the "safe-play" extreme value approach is built in to the traditional travel cost method. Still, our more systematic approach that uses additional ordinal information can improve even the lower bound estimate by assigning a strictly positive weight whenever the respondent ranks our destination *j* as his/her primary destination.

4. EMPIRICAL EVIDENCE

We applied the extreme value approach to survey data of a zonal TCM analysis of the Bellenden Ker National Park in Australia reported by Nillesen et al. (2002). Since the proportion of MDT respondents was as high as 48 per cent in this application, it proves a fruitful case for examining the impact of ignoring the MDT.

The survey included questions about the number of sites visited and respondents were asked to rank up to five places visited during the trip. Of the total of 482 questionnaires posted, a total of 96 were returned unopened. A total of 142 responses were received, representing a fair response rate of 36.8 percent.

4.1 Selecting the demand function form

Given the data set, the first step of the empirical analysis was to estimate the demand function. The traditional estimation technique is the Ordinary Least Squares (OLS). Unfortunately, the economic theory does not forward much useful guidelines for the specification of the function form for the recreational demand of e.g. a national park, besides the fact that the demand curve should be downward sloping since the recreational trips are clearly a normal good. We therefore did not restrict to a single "ideal" model, but experimented with multiple approaches. We applied the OLS technique to various different function forms, to identify the best fitting one, but also a non-parametric trapezoid-rule approach (Cooper, 2000), which does not impose any function form at all.

The advantages of the nonparametric technique are its theoretical consistency with the demand theory, and avoidance of strong ad hoc assumptions, which makes it very robust to specification errors. On the downside, the nonparametric estimators require a large sample size, and they are generally sensitive to sampling errors and data perturbations. We achieved a reasonable sample size of 142 observations by ignoring the zonal structure imposed in Nillesen et al. (2002). Moreover, we investigated the exposure to sampling errors by bootstrapping. Nevertheless, the problem of possible data perturbations still remains. We find the demand quantities highly reliable, but for some visitors, the actual travel costs can differ from the travel costs Nillesen et al. (2002) had estimated per each zone. The OLS error term may be better able to accommodate the possible data errors. The main problem of OLS is the sensitivity of the CS estimates to the (ad hoc) specification of the function form.

As a conclusion, we fail to prioritize one approach over another, and we hence report both the OLS and non-parametric estimates for cross-checking each other. In principle, if two very different approaches yield similar results, we can be better reassured that the estimates are not completely out of line.

4.2 OLS demand curve

Systematic testing revealed that the visitation rate, *VI,* per thousand inhabitants per zone j, VI_j, can best be described by a reciprocal functional form of the zonal travel costs TC_j only (Appendix A). For the purpose of comparison the same functional form will be used for the extreme value approach:

$$VI_j = a + \frac{b}{TC_j} \tag{8}$$

As maximum expected values are based on the ranking position, i.e. the method would not allow for a maximum value 'zero' to be assigned to any destination, the initial number of eighteen zones could be maintained. Analogously, zones with minimum expected values have been used for regression analysis. Those zones for which the average minimum expected value appeared to be zero were omitted from the data set. Thus, a total of thirteen zones were used for regression analysis using the minimum expected value approach.

When we inspected the residuals of the regression equation estimated with the standard OLS technique more closely, we discovered that zones with a high population tended to be associated with positive errors while low-population zones were matched with negative errors. Hence, even though the predicted visitation rates were unbiased, the total number of visitors turned to be hugely overestimated. As a consequence, the CS estimates based on the OLS figures were also biased upwards.

To obtain unbiased demand and CS estimates, we estimated the parameters *a* and *b* of Equation 8 again using the Weighted Least Squares (WLS) technique. Instead of the unweighted sum of squares of the error terms minimized by OLS, we minimized the weighted sum of squares of residuals, using the proportions of the zonal population to the total population as the weights. This yields unbiased estimates of the total number of visitors, and hence more reliable CS estimates. Table 1 reports the summary statistics for the extreme value (min and max) approach, and compares to the results treating MDT as single destination trips (i.e., ignores MDT treatment).

Insert: TABLE I Summary Statistics of the WLS Regressions Using Different MDT Approaches.

If we look at the empirical fit (Table I), then the best results were obtained by ignoring the MDT. From the econometric point of view this is nothing surprising, recalling that our MDT treatment decreases the variance of prices (travel costs) in the sample. In the Max case the fit is still very good, but the Min case is quite disappointing. In all three cases, the parameter estimates for the slope b are statistically significant at very high confidence levels, while the estimates of the intercept a have huge standard errors, and hence fail the significance test in all cases.

The estimated equations have been used to calculate total predicted visitation, at increasing entrance fees, and corresponding consumer surplus. By taking the definite integral over the zonal inverse demand functions and summing over all zones, we obtain the consumer surplus as:

$$CS_{OLS} = \sum_{j} \left[\left(\hat{b} \cdot \ln(k) - \hat{a} \cdot k \right) - \left(\hat{b} \cdot \ln(p_j) - \hat{a} \cdot p_j \right) \right] \cdot P_j \qquad (9)$$

where k is the choke price at which demand equals zero, P is the population, and x_j the average travel cost from zone j. Table 2 reports the estimated CS per visit for each of the three MDT scenarios.

INSERT: TABLE II Consumer Surpluses Estimated from OLS Demand Curve

INSERT: TABLE III Testing Statistical Significance of the CS Differences

The results show that using the minimum value approach results in a very large difference compared to treating multi-destination visitors as single destination visitors, $MDT \square SDT$, or using the maximum value approach. The difference is more than 470 percent. The difference between $MDT \square SDT$ and the maximum approach by about 20 percent is relatively small. The large differences in consumer surplus strengthen the argument to pay specific attention to MDT in applied TCM with a high fraction of MDT visitors, although the differences in consumer surplus are statistically insignificant at the ten per cent level.[3]

We next considered the magnitudes of the direct and the indirect effect. In case of the OLS-regressions, they can be calculated by using Equation (10) and Equation (11):

$$DE_{OLS} = CS_{OLS}^{M} - \sum_{j:p_j^O \le k} \left[\left(\hat{b}^M \cdot \ln(k) - \hat{a}^M \cdot k \right) - \left(\hat{b}^M \cdot \ln(p_j^O) - \hat{a}^M \cdot p_j^O \right) \right] \cdot P_j \quad (10)$$

[3] The standard error of the estimated consumer surpluses was calculated using the approach mentioned by Adamowicz et al. (1989)

$$IE_{OLS} = CS_{OLS}^{O} - \sum_{j:p_j^O \leq k} \left[\left(\hat{b}^M \cdot \ln(k) - \hat{a}^M \cdot k \right) - \left(\hat{b}^M \cdot \ln(p_j^O) - \hat{a}^M \cdot p_j^O \right) \right] \cdot P_j \quad (11)$$

Table IV reports the magnitudes of these effects for the min and the max cases. The table illustrates starting from the MDT-corrected (min or max) CS estimate the subtraction of the direct effect and subsequently the addition of the indirect effect to arrive at the $MDT \square SDT$ CS estimate. In the min-case the indirect effect dominates, and hence the $MDT \square SDT$ estimate is greater than the MDT-corrected one. Conversely, in the max-case dominates the direct effect and hence ignoring MDT leads to a lower CS estimate.

Insert TABLE IV

It is important to note the relatively high levels of these two offsetting effects compared to the levels of the CS estimates. (Note that $DE \leq CS^M$ and $IE \leq CS^O$.) As a consequence, the CS estimates are highly sensitive in the sense that a minor estimation error in either effect, the indirect effect in particular, can have a major impact on the CS estimates. This is aptly illustrated by our results: even when applying the same estimation method and the same data, the way of allocating the travel costs of MDT visitors leads to dramatic differences in the relative magnitudes of the direct and indirect effect, i.e., in the min-case the indirect effect is determinant whereas in the max-case the direct effect dominates.

As a final remark, we suspect that the high levels of the direct and indirect effect compared to the CS estimates are at least partly due to the curvature of the estimated demand function. According to our econometric model, the own price elasticity of recreational demand for the present nature park is relatively high, that is, demand drops rapidly as the price increases. Still, there are visitors who are observed to pay considerable sums of money (i.e., travel across the continent) to visit the park.

Consequently, the estimated demand functions are highly non-linear (convex). If the demand functions were linear, as in Figure 1, then these two offsetting effects would tend to be smaller compared to the CS estimates.

4.2 Non - parametric demand function

Next, the demand function was estimated in the non-parametric fashion to obtain a conservative estimate of the CS. Due to the small number of zones, we pooled all zones together for this exercise and in contrast to the OLS regressions did not estimate zone-specific demand functions but the overall demand curve using the actual numbers of visitors, and the travel costs estimated for each zone. Due to the limited sample size, no demographic variables were considered.

Our approach builds on the following two assumptions: 1) Every visitor is willing to pay any price less than or equal to the observed price. 2) No visitor is willing to pay a higher price. Under these two intuitive assumptions, we obtain the nonparametric estimates of the demand functions and the consumer surplus. The computational procedures are described in more detail in Appendix B.

Figure II illustrates these piece-wise linear demand functions for all three cases considered (plotting the inverse demand like in Figure I). In all three cases, demand is very sensitive to price changes at low price levels. Still, the max-case and especially the $MDT \square SDT$ scenario suggest that small but persistent demand exist even at very high price levels.

Insert Figure II: Piece-wise linear inverse demand curves estimated in nonparametric fashion.

Table V reports the CS estimates for the min- and max-cases, and their decomposition into the direct and indirect effect, resulting as the $MDT - SDT$ estimate. Overall, our nonparametric CS estimates come relatively close to our parametric OLS estimates, which provides us extra reassurance that our estimates should not be too far off. However, in contrast to the OLS case, the indirect effect is found to strongly dominate both in the min and max scenarios. In other words, ignoring the MDT seems to lead to a substantial overestimation in this case. The levels of the two effect are very high in the min scenario, but the max case seems much more robust to these effects.

Insert TABLE V

Unfortunately, there is no tractable analyticaly method of testing hypotheses and deriving confidence intervals within this nonparametric framework. Therefore, we resorted to the bootstrapping approach (Efron, 1979), the standard technique in the nonparametric literature. Assuming the uniform density over the observed price range, we drew 2000 pseudo-samples, size 18 observations like the original sample, from the empirical piece-wise linear demand curve for each of the three cases. We subsequently applied the same nonparametric method to fit the piece-wise linear demand curve to each pseudo-sample, and calculated the consumer surplus. The distribution of CS values in the set of these 2000 pseudo-samples should hence give us an idea of magnitudes of the sampling bias and standard error in the original estimation.

Insert TABLE VI

Table VI reports the key statistics from the bootstrapping analysis. The bootstrapping results suggest a relatively large standard error in the results, from

8.65% ($MDT \square SDT$) up to 35.9% (min) of the mean. It also revealed a significant downward bias in the estimates, from 5.2% ($MDT \square SDT$) all the way to 61.9% (min). That is, the mean CS value of the bootstrap pseudo-samples was in all cases significantly lower than the original CS estimate. Therefore, if our pseudo-sampling procedure reasonably mimics the actual sampling procedure, we may expect our original estimate to be similarly downward biased. Consequently, we adjusted our CS estimates upwards by the measured bias factor.

We can also derive confidence intervals directly from the simulated error distribution. Comparing the confidence intervals, we find that the differences between the CS estimates in the three scenarios are convincingly statistically significant at the 95 per cent confidence level. Note that the error distribution need not be symmetric or conform to normality, and hence our point estimates do not generally coincide with the median value of the confidence interval.

5. CONCLUSIONS

The treatment of MDT as SDT can result in a biased, either positive or negative, estimate of the consumer surplus. Most of the empirical evidence indicates a positive bias, indicating that treating MDT as SDT results in an underestimation of the consumer surplus. We show this will not always be the case. In our example recognizing MDT by applying the extreme value approach reduces the consumer surplus. In the non-parametric case we observe a significant upward bias of more than 300 percent.

The minimum value approach is well in line with the often-used approach of excluding MDT. While excluding the MDT from the sample may result in a biased consumer surplus calculation, which can be very large, as others and we have shown, the minimum value approach can be applied including MDT and their characteristics.

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APPENDIX A

Six different functional forms of the trip demand function have been tested, first with socio-economic variables included, however as they appeared to be insignificant in all but one case, a second regression was ran for each form with only travel costs included. Results for all three cases have been displayed in Tables A1, A2 and A3 respectively.

Clearly, the model with inverse travel cost outperformed all other models in terms of LL, adjusted R^2, and F- and t-values, for max, min and total travel costs. We have thus chosen to proceed, for all three cases, with a reciprocal form. Furthermore, as mentioned before, due to the fact that the socio-economic variables appeared to be insignificant, we decided they had to be discarded.

TABLE AI

Testing of Six Functional Forms for Max Values

Functional form	Variables included	LL	R^2adj	F-value	t-value C	t-value TC	t-value edu	t-value income	t-value age	t-value TC^2
linear	all	-39.26	0.04	1.2	1.56	-1.61	-1.18	-0.2	-0.37	
linear	tc	-40.59	0.09	2.88	2.66	-1.70				
log tc	all	-32.18	0.57	6.51	3.91	-4.61	-0.88	-0.85	0.01	
log tc	tc	-33.17	0.61	27.09	5.64	-5.21				
log vi	all	-32.78	-0.01	0.97	0.78	-1.11	-1.4	0.13	-0.13	
log vi	tc	-34.24	0.03	1.66	-1.56	-1.29				
log tc/log vi	all	-30.54	0.21	2.16	1.68	-2.29	-1.14	0.33	-0.27	
log tc/log vi	tc	-31.45	0.29	8.08	2.12	-2.84				
tc ^2	all	-34.49	0.39	3.18	1.94	-3.33	-1.62	-0.88	1.07	2.9
tc ^2	tc	-36.81	0.37	5.97	4.19	-3.26				2.8
1/tc	all	-18.14	0.91	43.23	-0.76	12.25	0.35	0.04	0.64	
1/tc	tc	-18.47	0.92	204.44	-1.43	14.30				

*Notes:
'LL' = Log-Likelihood
'tc' = travel costs
'vi' = visitation rates

Table AII

Testing of Six Functional Forms for Min Values

Functional form	variables included	LL	R^2 adj	F-value	t-value C	t-value TC	t-value edu	t-value income	t-value age	t-value TC^2
Linear	all	-28.39	0.14	1.48	0.86	-1.76	-1.41	0.51	0.67	
Linear	tc	-30.18	0.18	3.56	2.84	-1.88				
log tc	all	-26.20	0.39	2.88	2.17	-2.75	-1.36	0.61	0.72	
log tc	tc	-28.09	0.40	9.05	3.39	-3.01				
log vi	all	-18.92	0.42	3.2	0.47	-1.79	-2.31	0.83	1.47	
log vi	tc	-23.74	0.12	2.62	-0.05	-1.62				
log tc/log vi	all	-16.70	0.59	5.32	1.78	-2.79	-2.41	1.86	0.81	
log tc/log vi	tc	-22.36	0.29	5.86	2.00	-2.42				
tc ^2	all	-26.15	0.30	2.04	1.22	-2.22	-1.28	0.12	0.99	1.70
tc ^2	tc	-28.80	0.27	3.18	3.26	-2.10				1.54
1/tc	all	-24.09	0.56	4.75	0.11	3.68	-1.05	0.84	0.35	
1/tc	tc	-25.66	0.59	18.18	-0.82	4.26				

*Notes:
'LL' = Log-Likelihood
'tc' = travel costs
'vi' = visitation rates

Table AIII

Testing of Six Functional Forms for Total Travel Costs

Functional form	variables included	LL	R^2	F-value	t-value C	t-value TC	t-value edu	t-value income	t-value age	t-value tc^2
Linear	all	-38.49	0.12	1.59	1.59	-2	-1.34	-0.28	0.07	
Linear	tc	-39.87	0.17	4.47	3	-2.11				
log tc	all	-29.19	0.69	10.37	4.52	-5.89	-1.08	0.37	-0.52	
log tc	Tc	-30.09	0.72	44.67	7.21	-6.68				
log vi	all	-31.86	0.09	1.42	0.86	-1.66	-1.54	0.31	-0.12	
log vi	tc	-33.47	0.12	3.22	-1.03	-1.8				
log tc/log vi	all	-27.65	0.43	4.21	2.2	-3.49	-1.24	-0.16	0.55	
log tc/log vi	tc	-28.66	0.48	16.81	3.2	-4.09				
tc ^2	all	-32.69	0.5	4.41	1.91	-3.89	-1.86	-0.34	1.37	3.3
tc^2	tc	-35.27	0.47	8.49	4.89	-3.79				3.16
1/tc	all	-13.21	0.95	77.15	-1.01	16.4	0.55	1.33	-0.13	
1/tc	tc	-14.46	0.95	328.45	-0.25	18.12				

*Notes:
'LL' = Log-Likelihood
'tc' = travel costs
'vi' = visitation rates

APPENDIX B

The nonparametric estimates of the demand functions are obtained as follows. First, rank the zones in ascending order according to the observed travel costs. Let the travel costs be denoted by $p_1 \le p_2 \le ... \le p_{18}$, and the corresponding visitor volumes by $x_1, x_2, ..., x_{18}$. Construct a cumulative index of the number of visitors as $X_1 \ge X_2 \ge ... \ge X_{18}$, where $X_j \equiv \sum_{i=1}^{j} x_i$. Value X_j indicates the actual number of visitors who have paid the price (travel cost) less than or equal to p_j, and hence it is reasonable to assume $\hat{x}(p_j) = X_j$. Using the trapezoidal-rule (see e.g. Cooper, 2000, p. 453, for further details), we obtain nonparametric, piece-wise linear demand functions as

$$\hat{x}(p) = \max_{j:p_j \le p} X_j + \left[\frac{p - \max\limits_{p_j \le p} p_j}{\min\limits_{p_j \ge p} p_j - \max\limits_{p_j \le p} p_j} \right] \left(\min_{j:p_j \ge p} X_j - \max_{j:p_j \le p} X_j \right) \tag{12}$$

Let $\overline{p}$ denote the weighted average of the zonal travel costs, using the number of visitors per zone as the weights. To calculate the CS estimate, we use $\overline{p}$ for the prevailing price level. By basic geometry, the nonparametric CS estimate is then given by

$$\begin{aligned} CS = & \sum_{j:p_j \ge \overline{p}} \left[X_{j+1}(p_{j+1} - p_j) + \tfrac{1}{2}(X_{j+1} - X_j)(p_{j+1} - p_j) \right] \\ & + \min_{j:p_j \ge \overline{p}} X_j \left((\min_{p_j \ge \overline{p}} p_j) - \overline{p} \right) + \tfrac{1}{2} \left((\min_{p_j \ge \overline{p}} X_j) - \hat{x}(\overline{p}) \right) \left((\min_{p_j \ge \overline{p}} p_j) - \overline{p} \right) \end{aligned} \tag{13}$$

The decomposition is obtained using the following formulas:

$$DE_{NP} = CS^M - \sum_{j:p_j^M \geq \overline{p}^O} \left[X_{j+1}^M (p_{j+1}^M - p_j^M) + \tfrac{1}{2} (X_{j+1}^M - X_j^M)(p_{j+1}^M - p_j^M) \right]$$

$$- \begin{bmatrix} (\min_{j:p_j^M \geq \overline{p}^O} X_j^M) \cdot \left((\min_{p_j^M \geq \overline{p}} p_j^M) - \overline{p}^O \right) + \\ \tfrac{1}{2} \left((\min_{j:p_j^M \geq \overline{p}^O} X_j^M) - \hat{x}^M(\overline{p}^O) \right) \cdot \left((\min_{p_j^M \geq \overline{p}^O} p_j^M) - \overline{p}^O \right) \end{bmatrix} \quad (14)$$

$$IE_{NP} = CS^O - \sum_{j:p_j^M \geq \overline{p}^O} \left[X_{j+1}^M (p_{j+1}^M - p_j^M) + \tfrac{1}{2} (X_{j+1}^M - X_j^M)(p_{j+1}^M - p_j^M) \right]$$

$$- \begin{bmatrix} (\min_{j:p_j^M \geq \overline{p}^O} X_j^M) \cdot \left((\min_{p_j^M \geq \overline{p}} p_j^M) - \overline{p}^O \right) \\ + \tfrac{1}{2} \left((\min_{j:p_j^M \geq \overline{p}^O} X_j^M) - \hat{x}^M(\overline{p}^O) \right) \cdot \left((\min_{p_j^M \geq \overline{p}^O} p_j^M) - \overline{p}^O \right) \end{bmatrix} \quad (15)$$

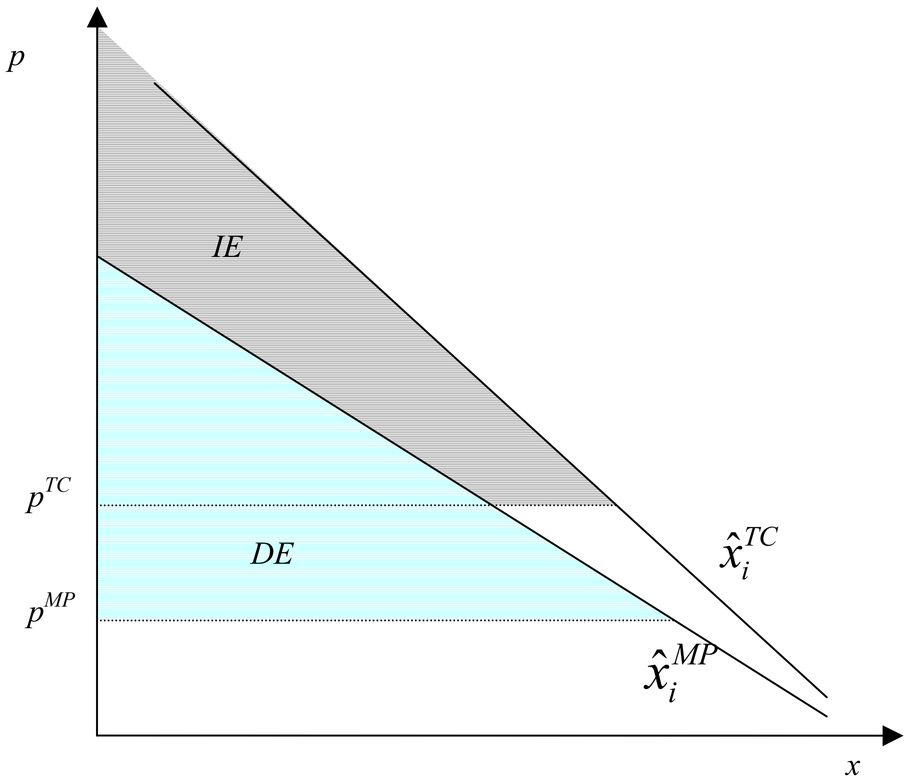

Figure I. Illustration of the direct and the indirect effects.

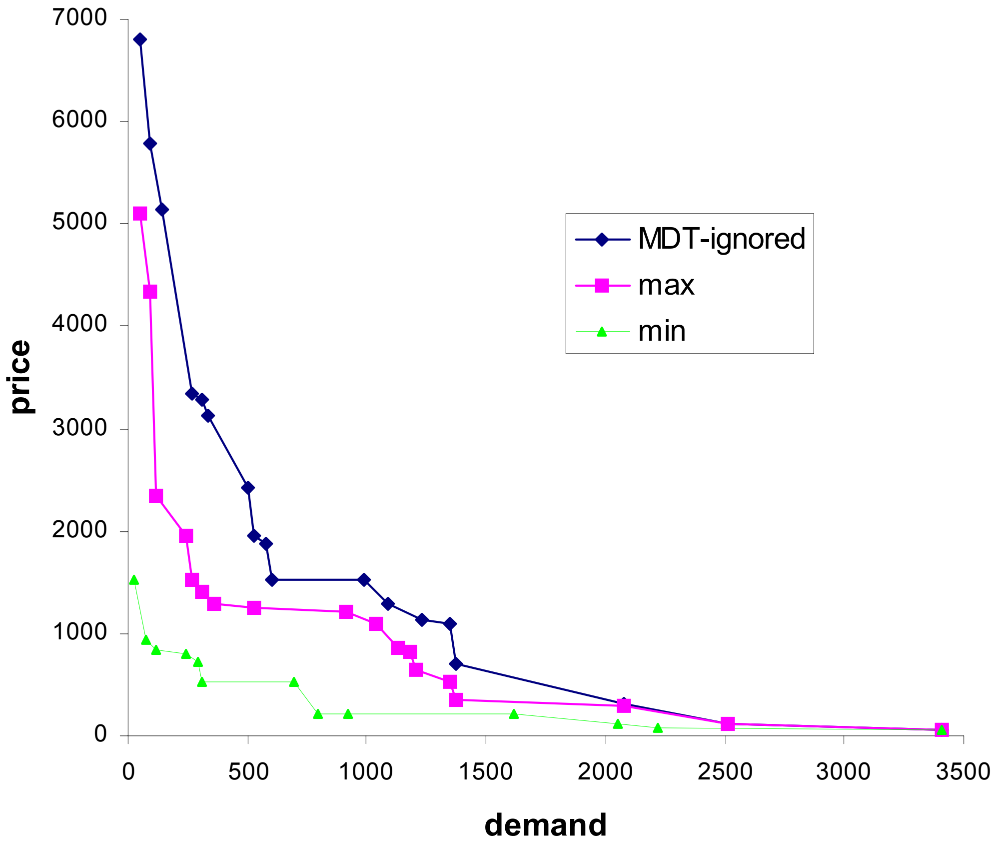

Figure II: Piece-wise linear inverse demand curves estimated in nonparametric fashion.

TABLE I

Summary Statistics of the WLS Regressions Using Different MDT Approaches.

	Min	Max	MDT □ SDT
R^2	0.279	0.887	0.945
F statistic	1.305	8.330**	17.197**
intercept $\hat{a}$	-0.388	-0.555	-0.283
st.error	5678577	256241	87043
slope $\hat{b}$	204.43**	549.43**	623.72**
st.error	0.180	0.012	0.004

* significant at 95% confidence level
** significant at 99% confidence level

TABLE II

Consumer Surpluses Estimated from OLS Demand Curve*

	Min	Max	MDT □ SDT
Choke price	527	990	2204
CS per visit	137	773	645

* All numbers are in AUD.

TABLE III

Testing Statistical Significance of the CS Differences

	Min vs. Max	Min vs. MDT □ SDT	Max vs. MDT □ SDT
t-test statistic	1.652	0.724	0.132
p-value	0.117	0.479	0.896

TABLE IV

Decomposition of the MDT-Effect: the Min and the Max Models.*

	Min	Max
CS^M	137	773
DE	(-) 113.4	(-) 713.1
IE	(+) 622.1	(+) 585.0
= CS^O	645	645

*All figures in AUD per visit.

TABLE V

Non-Parametric CS Estimates and their Decomposition.*

	Min	Max
CS^M	100	343
DE	(-) 93.3	(-) 116.3
IE	(+) 572.3	(+) 352.6
= CS^O	579	579

*All figures in AUD per visit.

TABLE VI

Bootstrapping Analysis

	Min	Max	MDT □ SDT
Point estimate:			
CS per visit	100	343	579
Sampling bias	(+) 62.0	(+) 25.0	(+) 29.7
= Bias corrected CS estimate	162	368	609
Std. error	13.67	39.95	47.56
95% confidence interval	(42 – 213)	(275– 416)	(475– 662)